Multilayer Clustered Sampling Technique (MLCS) for Near-Earth Asteroid Impact Hazard Assessment

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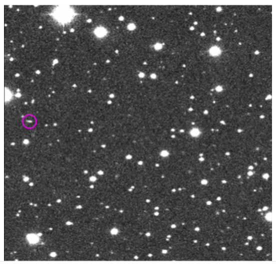
Impact Hazard Assessment

Introduction

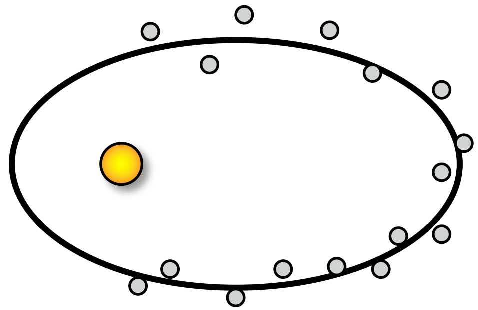
OBSERVATIONS



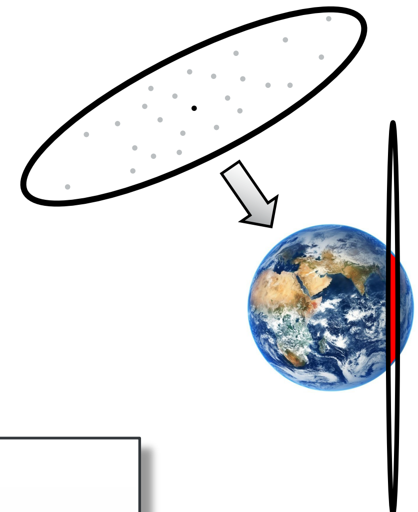
ASTROMETRY

Date	R.A.	Dec.
2019-01-14.53	23.5	30.0
2019-01-14.54	23.4	30.1
2019-01-14.55	23.3	30.2

ORBIT FIT



HAZARD ASSESS.



- Small probability (~10^{-7}).
- Distribution not necessarily Gaussian.
- Planetary encounters → Strongly nonlinear.
- To be implemented into an automatic system (Sentry).
- No human interaction.

Rare Event Detection

Generic problem

Probability Distribution → Orbital uncertainty (ics, physical param.,…) → $\mathbf{x} \in \mathbb{R}^d$

Physical Process → Propagate to close approach → $f(\mathbf{x})$

Threshold → C.a. dist. < Earth size → $f(\mathbf{x}) < \varepsilon$

Failure Region

$$\mathcal{F} = \{\mathbf{x} \in \mathbb{R}^d \mid f(\mathbf{x}) < \varepsilon\}$$

⚠ The failure region needs not be connected!

MLCS

Multi-Layer Clustered Sampling

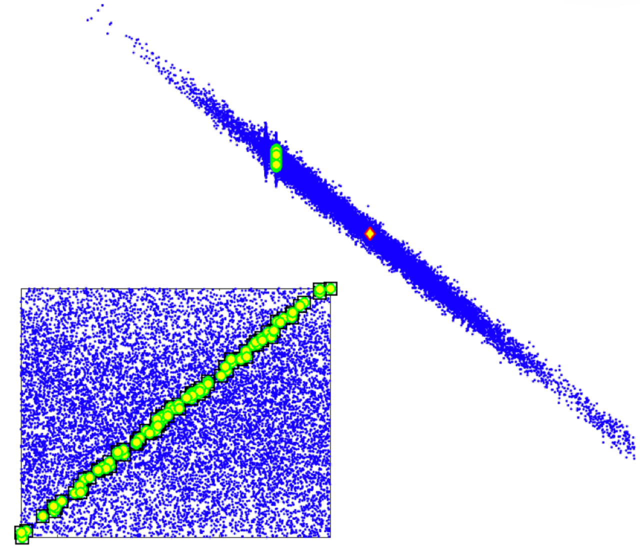
Locating $\mathcal{F}$

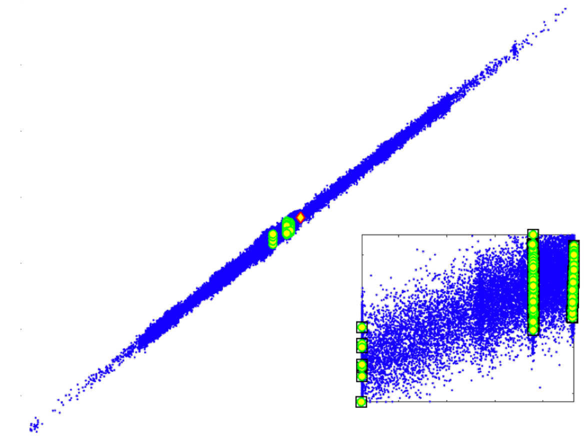
$$P = \frac{N_{\text{impacts}}}{N_{\text{samples}}}$$

If P is small $\Rightarrow$ $\mathcal{F}$ is small.
Locate a small subset of i.cs.

MLCS

- As accurate as Monte Carlo sampling.
- The smaller P, the greater the speedup.
- No need for proposal distributions.



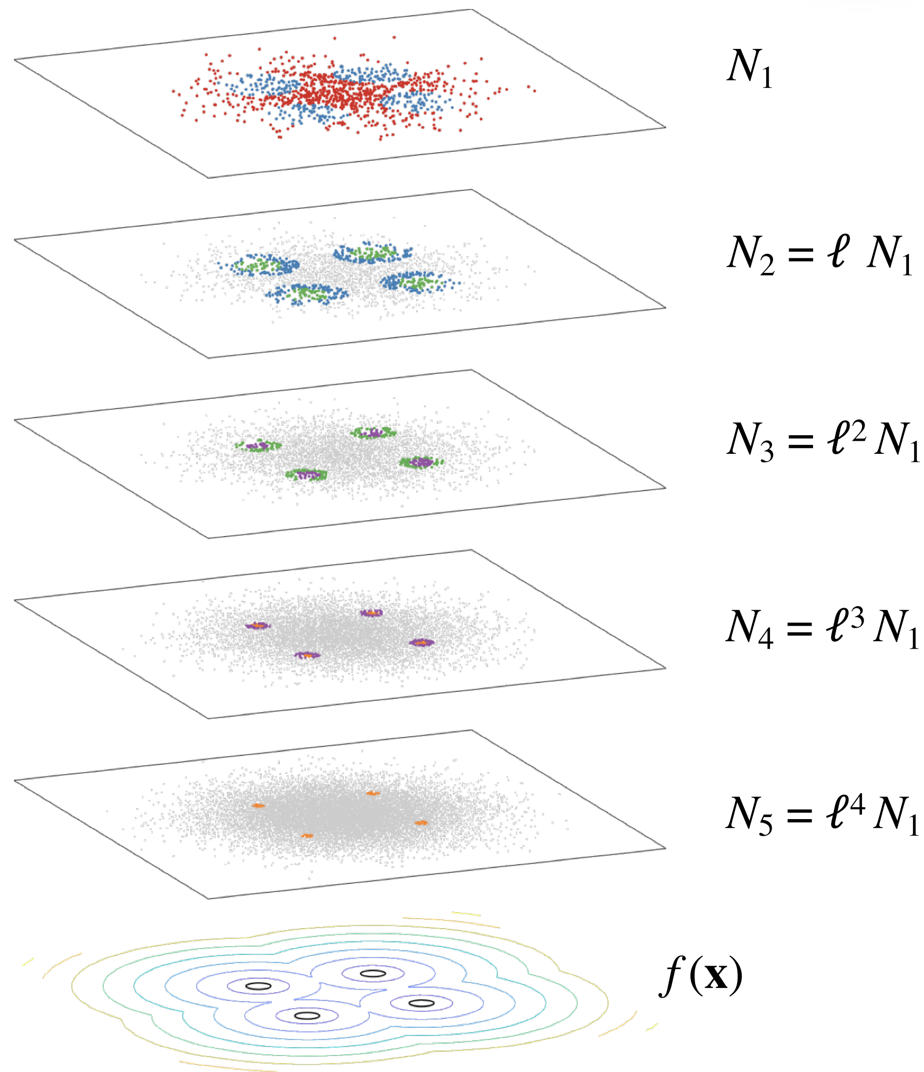


MLCS II

Multi-Layer Clustered Sampling

MLCS Algorithm

1. Sample layers
2. Evaluate $f(\mathbf{x})$ on layer 1.
3. Check convergence.
4. Select top p-percentile.
5. Cluster points.
6. Advance to the next layer.
7. Repeat 3-6 until converged.



Dynamical Regimes

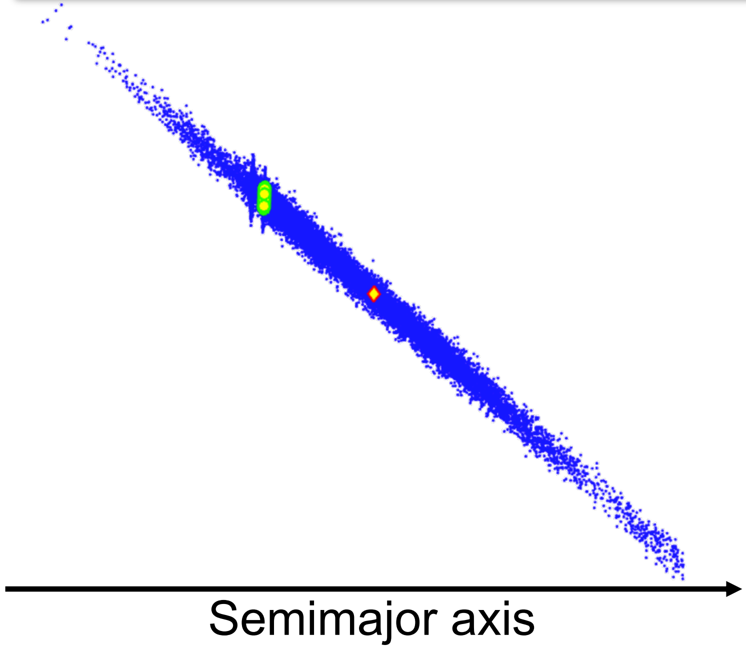
Clustering in orbital-element space

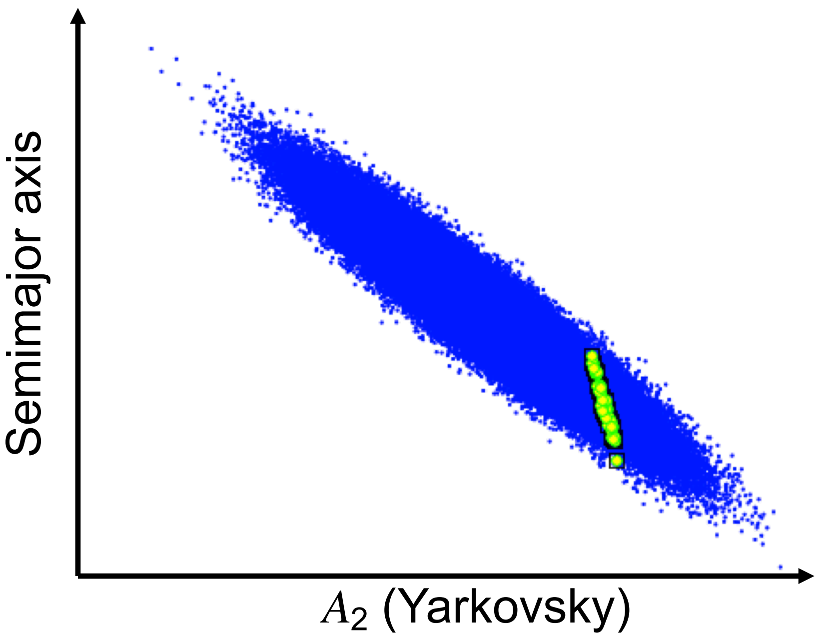
Orbital Elements

The uncertainty of the semimajor axis tends to dominate the failure region

Physical Parameters

The uncertainty of other physical parameters might play an even more important role

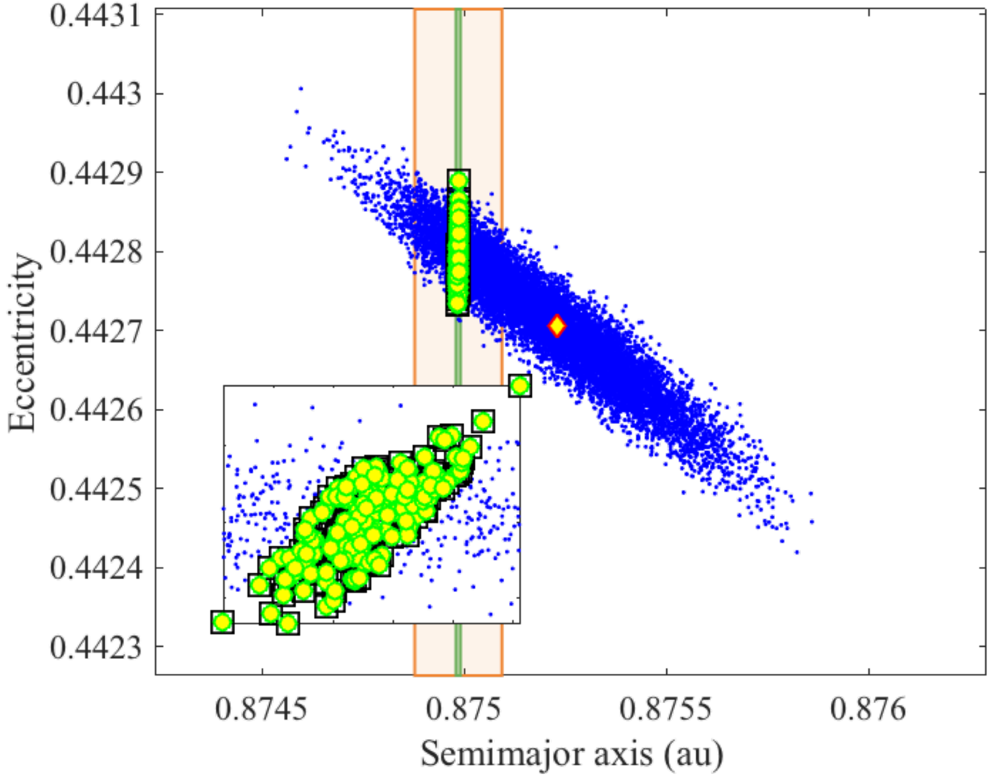




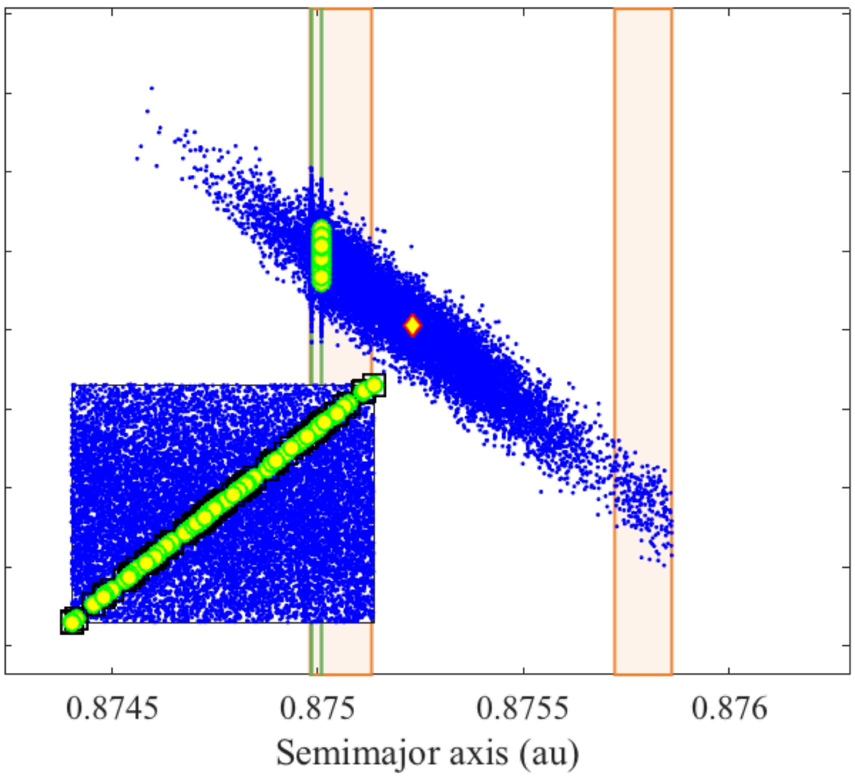
Example I

2017 RH16

$P = 9.9 \times 10^{-4}$ (2026-Aug-31)



$P = 5.1 \times 10^{-6}$ (2031-Sep-01)



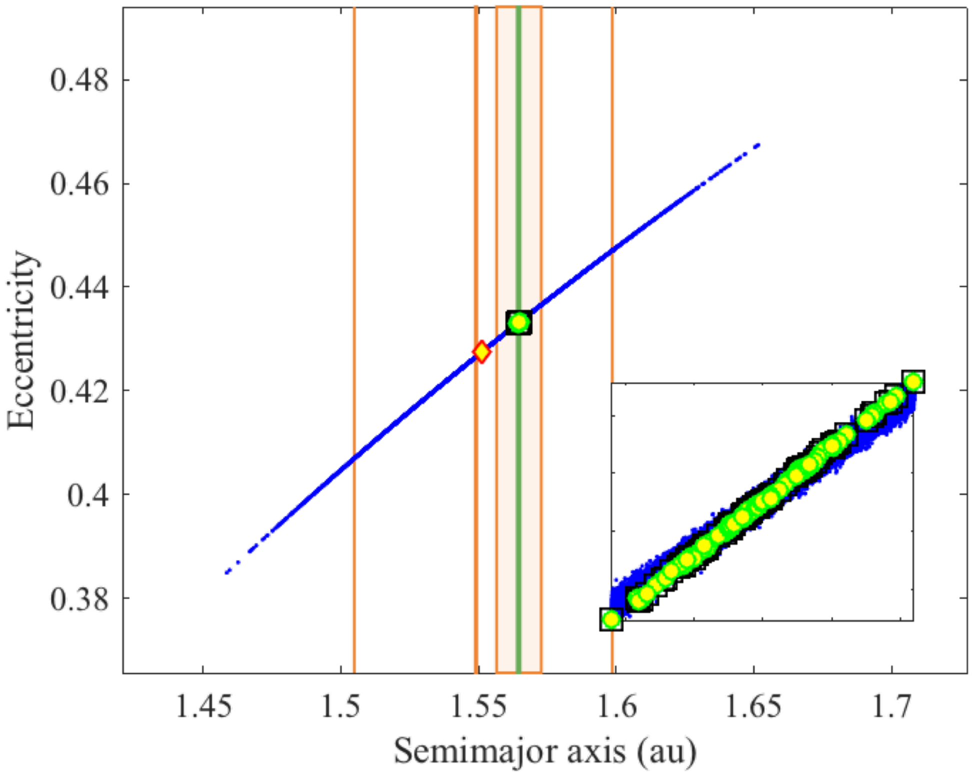
×10	Speedup (adaptive)
×1211	Speedup (absolute)

×276	Speedup (adaptive)
×276	Speedup (absolute)

Example II

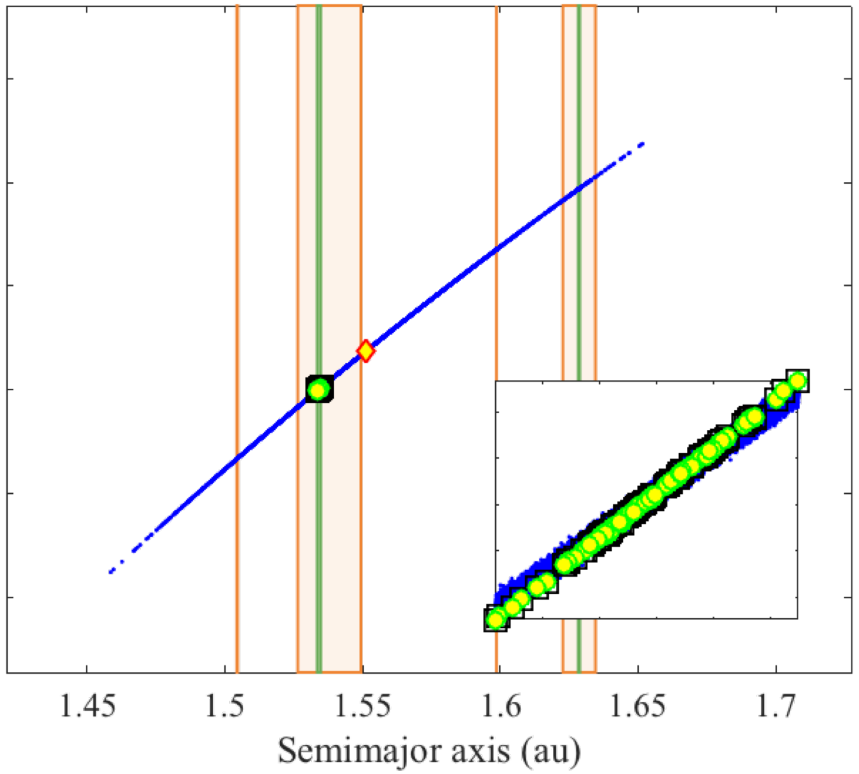
2013 YB

$P = 2.0 \times 10^{-5}$ (2023-Dec-24)



×33	Speedup (adaptive)
×131	Speedup (absolute)

$P = 2.1 \times 10^{-5}$ (2024-Dec-23)



×35	Speedup (adaptive)
×130	Speedup (absolute)

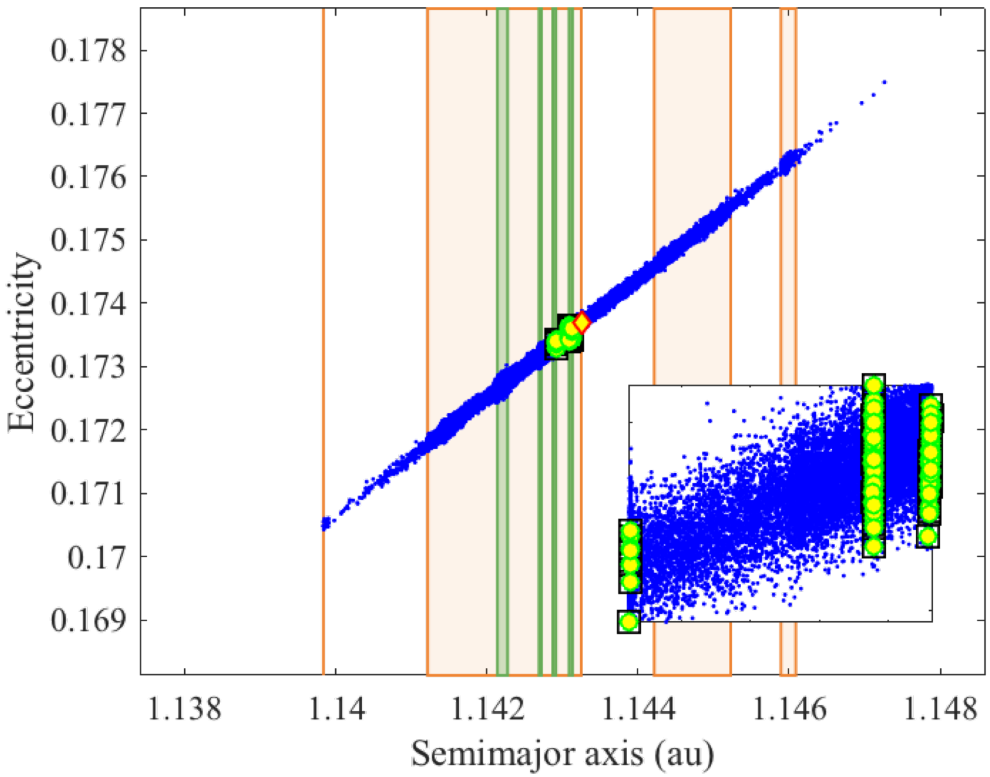
Example III

2018 UM1

$P = 1.4 \times 10^{-6}$ (2095-Jun-09.08)

$P = 1.8 \times 10^{-5}$ (2095-Jun-09.39)

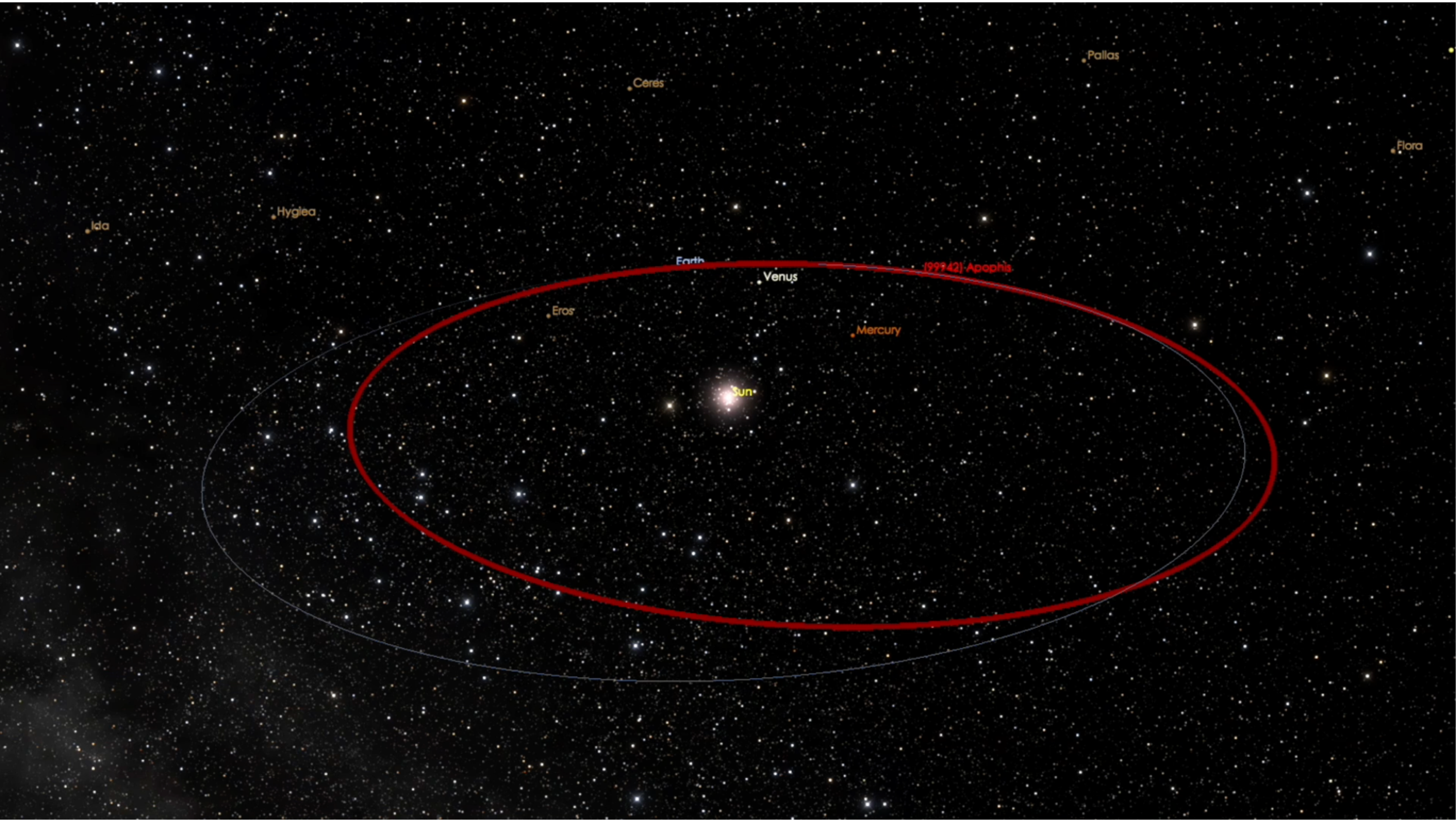
$P = 1.6 \times 10^{-5}$ (2095-Jun-09.40)



×15	Speedup (adaptive)
×61	Speedup (absolute)

Example IV

(99942) Apophis



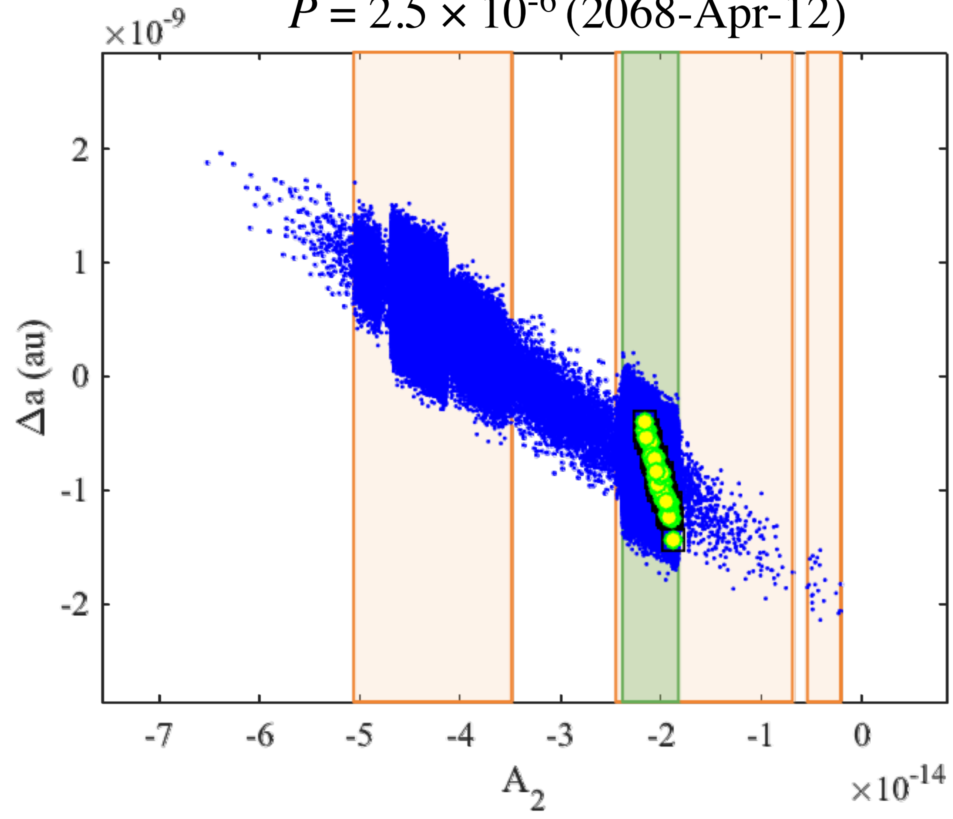
Example IV

(99942) Apophis

2068 Close Approach

- Strongly nonlinear due to 2029 close approach.
- Driven by the Yarkovsky effect.
- Linearized methods fail.

$P = 2.5 \times 10^{-6}$ (2068-Apr-12)



×12	Speedup (adaptive)
×12	Speedup (absolute)

Conclusions

MLCS as a generic algorithm

1. MLCS is an efficient alternative to Monte Carlo sampling:
   - Retains accuracy.
   - Significant speedups, especially for estimating low probabilities.
2. No assumptions about the uncertainty distribution.
3. No dynamical assumptions/simplifications.

MLCS for impact monitoring

1. Fully nonlinear.
2. Handles any source of perturbation.
3. Separates individual Virtual Impactors thanks to clustering.
4. Requires no human interaction (adequate for automatic systems).
5. Handles uncertain physical parameters.

“MLCS is an efficient alternative to Monte Carlo sampling”

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